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정보시스템 인력의 선발 및 평가를 위한 퍼지 ART 접근방법☆

A fuzzy ART Approach for IS Personnel Selection and Evaluation

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요 약

국제적 경쟁이 치열해지고 급속한 기술발전이 진행되고 있는 기업환경에서 좋은 정보시스템 인력을 선발하고 평가할 수 있는 방법은 매우 중요한 이슈이다. 그럼에도 불구하고 정보시스템 인력이 보유해야 할 지식과 스킬에 대해서는 많은 연구가 진행되었지만 이들 인력을 선발하고 평가하는 방법에 대해서는 그렇지 못한 것이 사실이다. 인력 선발은 정성적인 측정치와 정략적인 측정치 모두를 포함하는 다기준 의사결정 문제인데 본 연구에서는 정보시스템 인력의 스킬, 능력, 지식에 기초하여 이들의 선발과 평가 과정에서 이들을 분류할 수 있는 모형을 제시하였다. 본 모형은 신경망 알고리즘 모형에서 도출한 것으로서 Jaccard 선택함수 기반의 퍼지 ART 알고리즘을 적용하였다. 실제 인사자료를 활용하여 제안된 모형의 사용 용이성과 효과성을 검정해 본 결과 본 접근방법이 필드에서 충분히 활용될 수 있는 것으로 판단되었다.

주제어: 정보시스템 인력의 선발과 평가, 퍼지 ART, 다기준 의사결정, Jaccard 선택함수

ABSTRACT

Due to increasing competition of globalization and fast technological improvements the appropriate method for evaluating and selecting IS-personnel is one of the key factors for an organization's success. Personnel selection is a multi-criteria decision-making (MCDM) problem which consists of both qualitative and quantitative metrics. Although many articles have discussed various knowledge and skills IS personnel should possess, no specific model for IS personnel selection and evaluation, to our knowledge, has been published up to now. After reviewing the IS personnel's important characteristics, we propose an approach for categorizing the IS personnel based on their skills, ability, and knowledge during evaluation and selection process. Our proposed approach is derived from a model of neural network algorithm. We have adapted and implemented the fuzzy ART algorithm with Jaccard choice function. The result of an illustrative numerical example is proposed to demonstrate the easiness and effectiveness of our approach.

☞ keyword : IS personnel selection and evaluation; Fuzzy ART; ART model; Multiple Criteria Decision Making (MCDM); Jaccard choice function

1. Introduction

IS-personnel selection is a Multiple Criteria Decision Making (MCDM) problem which is affected by several conflicting factors. Consequently, human resource manager/ IS-manager must analyze the trade off among the criteria. And MCDM techniques support the decision-makers in evaluating a set of alternatives and deal with a selection process: by finding an optimal solution from a set of available alternatives according to a set of criteria. Selecting IS-personnel that will perform successfully in an organization is an important area for research. An improvement in selecting successfully performing personnel can increase revenues and profits while decreasing personnel turnover rates and financial losses [10]. IT Human Resource (HR) concerns, is still a big issue in the organization. How to identify recruit, and keep prized IT professionals with the skills companies' need most to compete in uncertain technology and business times. The main two issues involves in IT staffing are: whom to recruit and how to ensure the IT-staff has critical skills [5]. Ritu (2001) identified four strategies for determining whom to recruit:

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long term, balanced, high-performance, and short-term. Albert B. investigated that how companies ensure their IT staffs have the skills need to respond to rapidly changing and uncertain technological environment. But these studies only proposed the organizational strategies and selection criteria for IS-personnel [6]. After declaring the organization's strategy and selection criteria, the process of evaluating and selecting the appropriate IS-personnel comes out.

Although ART models have extensively studied and developed in the last thirty years and applied in different fields, their beneficial properties have not been used so far in Information System Personnel evaluation and selection process, i.e. categorizing of Information System Personnel. This study provides an alternative method for evaluating and selecting the appropriate IS-personnel. It describes fuzzy ART algorithm which enables classification and categorization of IS-personnel according to their similarity in Knowledge, Skills, and Abilities (KSA). To aid the process of categorizing IS-personnel, IS-personnel selection & evaluation approach based on modified fuzzy ART is proposed. The proposed model classifies candidates according to their similarity in each selection criteria rather than classifying according as traditional approach i.e. total average weight, and provides the prior candidate, recommended, and not recommended candidates.

The rest of this paper is organized as follows. Section 2 presents a brief overview of the characteristics and selection criteria of IS personnel along with Fuzzy ART algorithm. Section 3 shows our proposed model i.e. enhanced fuzzy ART algorithm to solve the IS personnel selection problem, along with the necessity for applying it. Section 4 presents the details of proposed algorithm. Conducted experiment in this paper is shown in section 5 with evaluation of model. Finally, conclusions with limitations and related topics for future researches, comes in section 6.

2. Literature Review

2.1 Criteria Selection

Determining the criteria is the first step in IS-personnel selection process. Keng (2010) identified 59 unique characteristics based on interview with 21 experienced IS-professionals and summarized 8 broad categories of critical characteristics of SI professionals in software development team: Working/ Cognitive abilities, Attitudes/ Motivation, Knowledge, Teamwork orientation, Interpersonal/ Communication skills, Management skills, Personality, and Professional orientation. The most prominent ones were Attitude/ Motivation, Knowledge, Interpersonal/ Communication Sills, and Working/ cognitive ability [1]. Ling (2005) applied hierarchy framework including Analysis & Design, Programming, Interpersonal, Business, and Environment and Application factors [4]. Mark (2008) selected the soft skills, specifically the personal attributes of problem-solving, critical thinking and team skills, are the most important skills for new IT-professionals. Furthermore the some essential technical skills were database knowledge and proficiency, knowledge of programming languages, object-oriented knowledge, and web development skills [3]. Kevin (2010) outlined 6 skills based on the data gathered by 20 researchers, interviewing 104 senior IT managers in 94 non-IT companies and categorized in two broad categories namely: Technical skills, and Non-technical skills [2]. Maisa (2009) applied standard hierarchical logic including operational, tactical and strategic to the profiles of IS/IT professionals [7]. Sang (2006) collected and analyzed 555 job advertisements posted on the corporate web sites of fortune 500 companies to understand the most up-to-date skill requirements for contemporary IT managers. Their result categorized the skills of IT managers n behavioral & technical skills [8][10]. IT is rapidly changing and evolving, often un-predicatively. So IT manager have difficulty in describing and analyzing specific profiles of the ideal IT candidate. Makoto (2007) presented a theoretical framework based on exploratory research, includes 3 IT skills perspective namely: the task-oriented perspective, fundamental perspective, and the socio-cultural perspective along with the managerial framework [9].

2.2 Fuzzy ART

The fuzzy ART is based on the adaptive resonance theory, and fuzzy set theory operations. Thus it operates by summarizing similar data into categories. Hence input values, as well as the weights of network links, can range only between zero and one. The Fuzzy ART neural network was first introduced by Carpenter et al. in 1991. The fuzzy ART is an unsupervised learning algorithm, which is capable of learning in both off-line and on-line training modes. It is the most recent adaptive resonance architecture, which is capable of rapid stable learning of recognition categories in response to arbitrary sequences of analog or binary patterns. The generalization to learning both analog and binary input patterns is achieved by replacing appearances of the set-theoretic intersection operator (∩) in ART1 by the MIN operator (∧) or fuzzy intersection of fuzzy set theory [14], while a related operation designated by (∨) is called the fuzzy-max operation.

Fuzzy ART neural network involves several differences in comparison with ART1 [16]:

1. Non-binary input vectors can be processed;
2. There is a single weight vector connection;
3. In addition to vigilance threshold (ρ), two other parameters have to be specified; choice parameters (α) and a learning rate (β) should be determined. Detail implementation of fuzzy ART is shown in Figure 1.

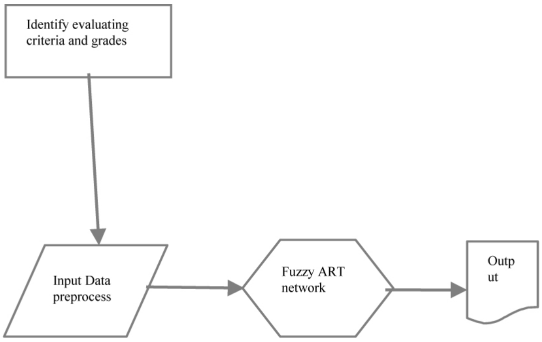
Recently, standalone Fuzzy ART network algorithm as well as hybrid algorithm have been applied in various areas of research such as supplier selection and evaluation [15][16], electric load forecasting [18], manufacturing quality control [19], pattern recognition [20], copyright verification scheme [21], passport recognition and face verification [22], image clustering method [23].

3. Personnel Selection and Evaluation based on modified Fuzzy ART

This study proposes Fuzzy ART algorithm with Jaccard choice function to solve the IS-personnel selection and evaluation problem proposed in section 1. The Fuzzy ART is based on the adaptive resonance theory, thus it operates by summarizing similar data into categories, and is based on fuzzy set theory operations. Thus we applied this ability to the IS-personnel selection and evaluation area.

The main characteristic of Fuzzy ART methodology is adaptation; algorithm controls the similarity between input values. By considering the vigilance parameter, it defines the membership of each input to the appropriate category [15]. This method can be applicable for determining the suitable IS-personals. Candidates are categorized according to their similarities with the aid of the vigilance parameter, by Fuzzy ART algorithm. The number and boundaries of resulting candidates' categories and category memberships of the IS-personnel are determined by the algorithm on its own.

According to the Fuzzy ART algorithm, as well as the principle of personnel selection, a model of IS-personnel selection and evaluation based on fuzzy ART is proposed in this paper, the specific process as shown in Figure 1.



(Figure 1) Fuzzy ART-based IS-personnel selection model

But there are some drawbacks of original fuzzy ART algorithm. When inputs are not prearranged, inconsistency exists between choice function and similarity (resonance) test, which may cause category proliferation problem. So we used the modified choice function with Jaccard Similarity coefficient, which is shown in following equation [17].

$$T_{i,a}(NI) = \frac{\sum_{j=1}^{n}(NI_{i,j} \wedge W_{i,j,a})}{\sum_{j=1}^{n} W_{i,j,a} \vee \sum_{j=1}^{n} NI_{i,j}}$$

Where, '∨' is the MAX operator in fuzzy logistics.

4. Algorithm

The modified Fuzzy ART algorithm for IS-personnel selection and evaluation is discussed stepwise in this section.

Phase 1: Determining team members, evaluation criterion and grading scale

Step 1) IT HR Strategy: Determining whom to recruit: Long-term, Balanced, High-performance, Short-term.

Step 2) Determining team members: The team is developed to identify criteria to evaluate candidates.

Step 3) Evaluating: The team determines the grading scale to rate each candidate according to the defined criteria.

Phase 2: Preprocess input data

Step 1) Normalization: Each input value is first normalized according to following equation to have value in the interval [0, 1], I==1⋯.M

$$NI_{i,j} = \frac{I(i,j) - \min(j)}{\max(j) - \min(j)}$$

Step 2) Complement coding: Proliferation of categories in Fuzzy ART is avoided if the inputs are normalized using the method of complement coding. Complement coding transforms an M-dimensional vector I into a 2M-dimensional system input vector. A complement-coded system input represents both the degree to which a feature I is present (ai) and the degree to which that feature is absent (1-ai).

$$A_c = (a_1, a_2, a_1, \ldots.. a_p, 1 - a_1, \ldots.1 - a_p)$$

Phase 3: Design parameter

Step 1) Initialize the network: Artificial Intelligence (AI) based models play important role in pattern categorization domains. The initial parameters should be determined by the team of the DMs. Parameters for the fuzzy ART algorithm are vigilance threshold (ρ) and choice parameter (α). ρ is responsible for the number of categories, where ρ∈ [0, 1]. If ρ is small, the result is inclined to a rough categorization. On the other hand, if ρ is chosen to be close to 1, many finely divided categories are formed and similarity in each category is much higher and choice parameter α is effective in category selection. These parameters are determined based on the type of the problem.

Step 2) Determination of initial weights: lower layer nodes are connected to output layer nodes through a weight vector. For each output category node j (j=1⋯⋯..N), there is a vector associated with layer of F1 nodes, w1= (wj1⋯ wj2M) of adaptive weights. The initial weights for nodes are taken 1 and the number of the category is set 1(ρ=1) i.e. wj1 (0) = ⋯. = wj2M (0) =1

this means that, each category is uncommitted.

Phase 4: Categorizing IS-personnel using the fuzzy ART

Step 1) Presentation of the normalized input vector [0, 1] to the network

Step 2) Computation of choice function: From normalization step, some of the values may change into 0, which can be treated as non-prearranged value by choice function, causes the proliferation problem. To overcome this drawback, the choice function T_j for each category j, is computed by

$$T_{i,a}(NI) = \frac{\sum_{j=1}^{n}(NI_{i,j} \wedge W_{i,j,a})}{\sum_{j=1}^{n} W_{i,j,a} \vee \sum_{j=1}^{n} NI_{i,j}}$$

Where the fuzzy intersection operator '∧' and union '∨' are defined by

$$(x \wedge y) = \min(x, y)$$
$$(x \vee y) = \max(x, y)$$

Step 3) Selection of maximum choice function value: The maximum choice function value is selected by:

$$T = \max\{T_{i,a} : a = 1, 2, \ldots\ldots, m\}$$

Step 4) Resonance or rest test: An important quantity related to the Fuzzy ART algorithm is the category match function and determines the appropriate category for the input also called resonance or rest test. This is the value of the jth node, with respect to an input pattern I used in comparison to the vigilance parameter ρ ∈ [0, 1]. The matching function is computed by:

$$M_{i,p}(T) = \frac{\sum_{j=1}^{n}(NI_{i,j} \wedge W_{i,j,a})}{\sum_{j=1}^{n} W_{i,j,a} \wedge \sum_{j=1}^{n} NI_{i,j}}$$

Step 5) Mismatch resetting vigilance test: If resonance < ρ then the vlaue of the choice function T_j is reset to -1 for the duration of the input presentation. A new index j is chosen by step 8. The search process continues until the chosen j satisfies resonance <= ρ.

Step 6) Learning: The weight vector w_j is updated according to the equation

$$W_{i,j,p}^{(new)} = \beta\left(NI_{i,j} \wedge W_{i,j,p}^{(old)}\right) + (1-\beta) W_{i,j,p}^{(old)}$$

The learning rate β defines how quickly prototypes converge to the common minimum of all input patterns assigned to the same cluster. With β=1 the network is working in a fast learning mode, stabilizing the network state after a few presentations of all training patterns. In contrast, lower learning rates lead to a slow learning mode.

Step 7) Repeat: The algorithm continues with the next input at step 1. The algorithm ends by allocating all inputs to the categories.

Phase 5: Prioritization

Step 1) Category prioritization: The categorized candidates should be prioritized in this step. The arithmetic mean of the input values in each class is used for prioritization.

Step 2) Criteria prioritization: Then the desired criteria are prioritized from the prior category and further actions will be done by DMs team.

5. Algorithm Evaluation

5.1 Algorithm Evaluation with Actual Data

In this section, we illustrate the approach by using a numerical data example. Authors obtained data by interview and observation from an IT company which desires to hire IS-personnel. After initial screening, five candidates (alternatives) A1, A2, A3, A4, and A5 remain for further evaluation. A committee of decision makers has been formed to conduct the interview and to select the most appropriate candidate. Nine criteria from a global IT company, categorized into Leadership Standards and Experience Dimension, are considered. The decision makers use the rating variables as shown in table 1 to evaluate the candidates with respect to criteria Cj and the final grade of each candidate is as shown in table 3.

The above described fuzzy ART algorithm for IS-personnel selection and evaluation is executed using the data given in table 2. The choice parameter α is taken as very small, while learning rate is β=1.0. Vigilance parameter, which is directly related to the number of category, is set to ρ=0.73. These candidates are categorized into 3 categories as shown in table 3.

(Table 1) Scale for scoring the alternatives

Rating Variables	Scores
Outstanding	5
Excellent	4
Strong	3
Moderate	2
Opportunity for Growth	1

(Table 2) Scale for scoring the alternatives

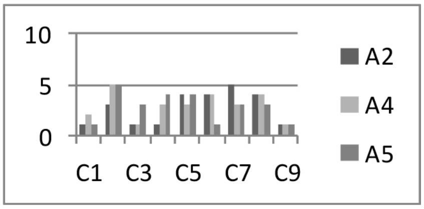
Category	Nr.	Criteria description	Candidates				
			A_1	A_2	A_3	A_4	A_5
			Scores				
Leadership Standards	C_1	Business Acumen	2	1	3	2	1
	C_2	Team Leadership	1	3	2	5	5
	C_3	Customer Centric/Team work	3	1	1	1	3
	C_4	Result & Performance Driven	5	1	3	3	4
Experience Dimensions	C_5	Company's Values	4	4	1	3	4
	C_6	Business Models	4	4	4	4	1
	C_7	Size Complexity	4	5	1	3	3
	C_8	Functional Skills	5	4	2	4	3
	C_9	Geography	1	1	3	1	1

A1 appears as the most appropriate candidate. It means that its assessment status is "Preferred". The company management can choose the candidate from category-A for the particular post. If more candidates are required to be recruited, recommended category B can be taken into account for Criteria prioritization as shown in Fig. 2. If team leader is most important criteria, than candidates A4, or A5 of category B can be recruited. And candidate A3, of category C, is not recommended to recruit for that post.

Candidates A2, A4, and A5 have different average weights but categorized in the same category according as their similarity in each criteria as shown in Figure 2. Traditional approach only categorizes hierarchically according as their average weights rather than similarity in each category.

(Table 3) Scale for scoring the alternatives

Category label	Candidate	Category	Priority measure
Category A	A_1	Preferred	3.222
Category B	A_2, A_4, A_5	Recommended	2.778
Category C	A_3	Not-recommended	2.222

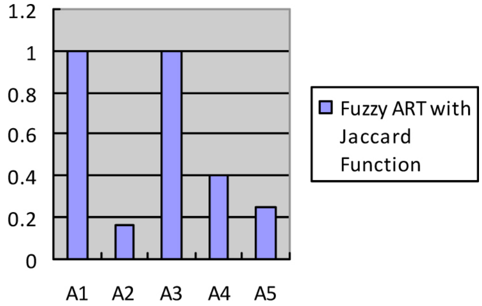


(Figure 2) Criteria prioritization for particular category

5.2 Performance Test

There are different kinds of cluster evaluation algorithms, among them silhouette coefficient has been widely used to analyze the performance of clustering algorithms. Silhouette refers to a method of interpretation and validation of clusters of data. The technique provides graphical representation of how well each object lies within its cluster [28]. We have measured this assessment, by implementing in MATLAB.

We have calculated the silhouette coefficient, which ranges between [-1, 1]. Silhouette coefficient with value of greater than 0, shows better classification, and less than 0, shows bad classification. The silhouette coefficients for various categorization cases for Fuzzy ART with Jaccard choice function is shown in figure 3. The average silhouette coefficient with Jaccard choice function is 0.5641. This figure shows the value of silhouette coefficient is very close to 1 and silhouette for each category is greater than 0.



(Figure 3) Silhouette Coefficient for each category

6. Conclusions

In this age of increasing competitive markets, and uncertain technology, selecting and evaluating the most appropriate IS-personnel is very important for an organization's success. In order to overcome the disadvantages of the traditional methods, this paper presents an IS-personnel selection and evaluation model based on fuzzy ART algorithm with Jaccard choice function. The algorithm is based on fuzzy set theory. Fuzzy set theory has been applied in selection and evaluation process in various areas and shows the better performance [25].

The recruiter's intention for selecting new technology for selection process is related to the extent to which the new technologies are believable and can be used with relatively low effort [24]. AI methods are better than traditional methods, because they are designed to act like human judgment [15]. Therefore, the decision maker (DM) should only provide the information needed for the system. This model can improve the quality of decision making and provide intelligence to traditional evaluation and selection of IS/IT personnel. The most important contribution of the proposed method was the ability of its clustering for the IS-personnel selection and evaluation problems. Also, the proliferation problem has been mitigated by using Jaccard choice function in place of original fuzzy ART choice function. The algorithm has been adaptive and has easily applied to firms and companies. This method has been very flexible, and number of categories can be varied by changing the vigilance parameter.

In conventional methods; although, all evaluation criterion (Leadership standards and Experience dimensions) are rated separately, the categorization of the IS-personnel are done based only on an aggregated value. Average value is used to measure Skills, Ability and Knowledge of the candidates. But two candidates that have exactly the same aggregate value can have totally different grades according to evaluation criteria. It means different candidates that have the same average score can be dissimilar from the candidate's Skills, Ability and Knowledge. In other hand, two candidates with different average value can be in the same category. There would be no meaning of separating criteria if the average score is calculated. Since it can causes loss of criteria's separated effects and failures in evaluation process. In proposed modified Fuzzy ART IS-personnel selection and evaluation algorithm, all evaluation criteria ratings are taken into the account separately for each candidate to place them in the most appropriate group. So the candidates with relatively lower average score can be classified into relatively higher candidate category or vice versa. This contribution of the algorithm is very important and useful. The propose method is effective to deal with IS-personnel evaluation and selection problem. This method not only selects the most appropriate candidates but also clusters all of the candidates according to their similarity.

Reference

[1] K. Saiu, X. Tan, and H. Sheng, "Important characteristics of software development team members: an empirical investigation using Repertory Grid," *Info Systems J*, Vol 20, No. 1, pp. 563-580, 2010.

[2] KP. Gallagher, KM. Kaiser, JC. Simon, CM. Beath et al., "The Requisite variety of Skills for IT Professionals," *Communication of the ACM*, Vol 53. No.4, pp. 144-148, 2010.

[3] ME. McMurtrey, JP. Downey, SM. Zeltmann et al., "Critical Skill Set of Entry-Level IT Professionals: An Empirical Examination of Perceptions from Field Personnel," *Journal of Information Technology Education*, Vol 7, pp. 101-120, 2008

[4] LS. Chen, and CH. Cheng, "Selecting IS personnel use fuzzy GDSS based on metric distance metho," *European Journal of Operational Research*, Vol 160, pp. 803-820, 2005.

[5] AB. Schwarzkopf, RJ Mejias, CS. Saunders et al., "Effective Practices for IT Skills Staffing," *Communications of the ACM*, Vol 47, pp. 83-88, 2004.

[6] R. Agrawal, and TW. Ferratt, "Rafting an HR Strategy to Meet the Need for IT Workers," *Communication of the ACM,* Vol 44, pp. 58-64, 2001.

[7] MM. Silva, and APCS. Costa, "Profile of Brazilian IS/IT professionals: Hierarchical and decision levels in an organization," *Technology in Society,* Vol 31, pp. 305-314, 2009.

[8] S. Lee, and C. Lee, "IT Manager's Requisite Skills," *Communications of the ACM,* Vol 49, pp. 111-115, 2006.

[9] M. Nakayama, and NG. Sutcliffe, "Perspective-driven IT talent acquisition," *ACM SIGMIS-CPR,* pp. 172-178, 2007.

[10] ML. Gargano, RA. Marose, and L. Kleeck, "An application of artificial neural networks and genetic algorithms to personnel selection in the financial industry," *IEEE,* pp. 257-262, 1991.

[11] PA. Todd, JD. Mckeen, RB. Gallupe, "The evolution of IS job skills: A content analysis of IS job advertisements from 1970-1990," *MIS Quarterly,* Vol 19, pp. 1-27, 1995.

[12] GA. Carpenter, and S. Grossberg, "Adaptive Resonance Theory," *CAS/CNS Technical Report,* pp. 1-23, 2009.

[13] Y. Cao, and J. Wu, "Dynamics of projective adaptive resonance theory model: the foundation of PART algorithm," *IEEE Transactions of Neural Networks,* Vol 15, pp. 245-260, 2004.

[14] GA. Carpenter, S. Grossberg, and DB. Rosen, "Fuzzy ART: Fast stable learning and categorization of analog patterns by an adaptive resonance system," *Technical Report in CAS/CNS,* 1991.

[15] GA. Keskin, S. Ilhan, and C. Ozkan, "The Fuzzy ART algorithm: A categorization method for supplier evaluation and selection," *Expert Systems with Applications,* Vol 37, pp. 1235-1240, 2010.

[16] M. Ghorbani, SM. Arabzad, M. Bahrami, "Applying a Neural Network algorithm to Distributor selection problem," *Procedia-Social and Behavioral sciences,* Vol 41, pp. 498-505, 2012.

[17] RG. Ozdemir, G. Gencyilmaz, and T. Aktin, "The modified fuzzy art and a two-stage clustering approach to cell design," Information *Sciences,* Vol 177, pp. 5219-5236, 2007.

[18] MLM. Lopes, CR. Minussi, abd ADP. Lotufo, "Electric load forecasting using a fuzzy ART&ARTMAP neural network," *Applied Soft Computing*, Vol 5, pp. 253-244, 2005.

[19] M. Pacella, Q. Semeraro, and A. Anglani, "Manufacturing quality control by means of a Fuzzy ART network trained on natural process data," *Engineering Applications of Artificial Intelligence,* Vol 17, pp. 83-96, 2004.

[20] MH. Kim, DS. Jang, and YK. Yang, "A robust-invariant pattern recognition model using Fuzzy ART," *Pattern Recognition,* Vol 34, pp. 1685-1696, 2001.

[21] CY. Chang, HJ. Wang, and SW. Pan, "A robust DWT-based copyright verification scheme with Fuzzy ART," *Journal of Systems and Software,* Vol 82, pp. 1906-1915, 2009.

[22] KB. Kim, S. Kim, "A passport recognition and face verification using enhanced fuzzy ART based RBF network and PCA algorithm," *Neurocomputing,* Vol 6, pp. 213-133, 2007.

[23] SS. Park, KK. Seo, and DS. Jang, "Fuzzy art-based image clustering method for content-based image retrieval," *International Journal of Information Technology & Decision Making*, Vol 6, pp. 213-233, 2007.

[24] JK. Oostrom, DV. Linden, MP. Born & HT. Molen, "New technology in personnel selection: How recruiter characteristics affect the adoption of new selection technology," *Computers in Human Behavior*, Vol 29, pp. 2404-2415, 2013

[25] D. Yu, W. Zhang, & Y. Xu, "Group decision making under hesitant fuzzy environment with application to personnel evaluation," *Knowledge-Based Systems*, Vol 52, pp. 1-10, 2013.

[16] http://en.wikipedia.org/wiki/Silhouette_%28clustering%29

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